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ROBUST METHOD FOR SELF-CALIBRATION OF CAMERAS HAVING THE VARYING INTRINSIC PARAMETERS

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ABSTRACT

In this paper we present a new method of cameras self-calibration having the varying intrinsic parameters, by an unknown planar scene, and we demonstrate that the estimation of these parameters can be made from three matches between two images, which shows the importance of our approach at minimizing constraints on the self-calibration system (on the one hand, the cameras are characterized by varying intrinsic parameters, and on the other hand the use of only two images to estimate these parameters). The main idea of this method is based on the formulation of a non-linear cost function from the relationship between three matches which are the projection of three points representing vertices of parallelogram, and the relationship between the images of the absolute conic of the two images to estimate the intrinsic parameters of the different cameras. The performance of our approach in terms of accuracy and convergence is shown by the experimental results and the simulations realized.

Keywords*:* *Control Points, Matching, Homography, Self-Calibration, Varying Intrinsic Parameters, Non-Linear Optimization.*

1. INTRODUCTION

The cameras self-calibration is widely used in image processing and in several areas of computer vision, especially the 3D reconstruction, robotics, cinema, medical imaging. The self-calibration methods ([1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17]) can automatically calibrate the cameras used, but without any a prior knowledge on the scene. The general idea of most of these methods is to look for equations according to the invariants in the image and the intrinsic parameters of cameras, these equations are generally non-linear, and need two phases to solve them: initialization and optimization of a cost function.

In general, the problem of self-calibration methods is the proposal of several constraints on the self-calibration system (scenes, images, cameras), these constraints limit several studies in literature, for example the use of multiple images provides a large number of equations which require on the one hand powerful algorithms to solve them, and on the other hand require a long execution period of time to converge to the optimal solution. In addition, the studies based on self-calibration of cameras with constant intrinsic parameters remain restricted and limited in the domain of self-calibration of cameras characterized by varying intrinsic parameters.

In this work, an unknown planar scene is used to estimate the varying intrinsic parameters of cameras; the method is based on using three matches (between the couples of images) which are the projection of three points representing vertices of parallelogram. The homography matrix between each pair of images is determined from four matches by RANSAC algorithm [18], this matrix is used with the three matches to calculate the projection matrices of three points in different images by solving a system of linear equations. The different matrices calculated are used to show the relationship between the three matches and the relationship between images of absolute conic, and finally the formulation of a non-linear cost function. The resolution of this function by the Levenberg-Marquardt algorithm [19] allows estimating the varying intrinsic parameters of the different cameras used. This new method calibrates the cameras from two images only; in addition, the

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cameras are characterized by varying intrinsic parameters. Therefore, this method minimizes the constraints on the self-calibration system, and finally it solves some self-calibration problems mentioned in the previous paragraph.

The remainder of this article is organized as follows: The second part presents the related work. The third part explains the model of camera used. The cameras self-calibration is presented in the fourth part. The experimentations are presented in the fifth part and the conclusion is in the sixth part.

2. RELATED WORK

The self-calibration of cameras consists on determining the parameters of the transformation between the 3D scene coordinates and the image coordinates, and vice versa by an unknown scene. Several studies have been made in this axis : The paper [1], is based on self-calibration of cameras with constant intrinsic parameters by a planar scene, the idea of this method is the estimation of these parameters by the projection of two circular points in each image, and the determination of the homographies between the different images (five images at least). A practical method of self-calibration of cameras with varying intrinsic parameters is proposed in [2], this method can retrieve the metric reconstruction from a sequence of images, and the authors showed that the absence of skew alone is sufficient to calibrate the cameras used. In [3], the camera parameters are obtained by using the Kruppa equations. The singular value decomposition of the fundamental matrix gives a simple form of the Kruppa equations [4], which solves the problem of self-calibration of cameras with varying intrinsic parameters. A new method in [5], based on the movement of the camera which is characterized by constant intrinsic parameters except the focal length that varies freely between the different views. The problem addressed in [6] is the self-calibration of camera with varying focal length from the views of a planar scene whose Euclidean structure is unknown, the main idea of this method is to calculate both the intrinsic parameters of the camera and those related to the Euclidean structure of the observed scene, the formulation of the cost function is non-linear, which causes the problems with the initialization of the focal length, to solve these problems the authors proposed a new formulation that is independent of the focal length. The use of geometric constraints is the major idea discussed in [7], this method calculates the initial solution of the intrinsic and extrinsic parameters of the camera using geometric constraints on the first image, and the use of the second image permits to optimize the initial solution. In [8], a study realized on the different methods of self-calibration of cameras for 10 years until 2003, this study includes methods based on constant intrinsic parameters and those based on varying parameters. A new simple method [9] based on the fundamental matrix to estimate the focal lengths of two cameras, the authors assumed that the pixels are squared and the principal point is known (the centre of the image). The problem addressed in [10] is that of self-calibration of cameras with varying intrinsic parameters from image sequences of an object, this method is based on a constant movement between images of the rotating object around a single axis, the relationship between the projection matrices and those of the fundamental matrices provides camera parameters by solving a system of non-linear equations. In [11], the vanishing line is used in self-calibration of cameras characterized by constant intrinsic parameters, the resolution of three linear equations obtained from the circles and their respective center determine the vanishing line. The theory of these lines and circular points allow estimating the camera parameters. A new method of camera self-calibration is presented in [12], it is based on an unknown 3D scene to calibrate the camera with constant intrinsic parameters, A non-linear cost function is formulated from a motion of the camera "translation and small rotation" to estimate the homographies matrices of the plane at infinity between the pair of images; and the resolution of a linear cost function allows estimating the camera parameters. The problem addressed in [13] is self-calibration of cameras with varying intrinsic parameters, this method is based on the transformation of the image of the absolute dual quadric; this transformation is performed on all elements of the image of the absolute dual quadric to obtain the same magnitude for all these elements, which can make the solutions more stable. In [14], an approach of self-calibration of cameras with constant intrinsic parameters using vanishing line, the main idea of this method is to compute the vanishing line by solving three linear equations based on circles and their respective centres, and the theory of these lines and the circular points are used to calculate the intrinsic parameters of the camera. A new method of camera self-calibration treated in [15], this method is based on the relative distance of the scene and on the homography matrix that converts the projective reconstruction to the metric one, and whose elements depend on the camera intrinsic parameters. These parameters and

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3D structure are obtained by minimizing an error function that is related to the relative distance. In [16], a method of self-calibration of cameras with varying intrinsic parameters, based on the quasi-affine reconstruction, after this reconstruction, the homography of the plane at infinity can be determined, and used with constraints on the image of the absolute conic to estimate the intrinsic parameters of cameras used. A self-calibration method of cameras with a positive tri-prism is presented in [17], it is based on circular points which are obtained from properties of tri-prism, the camera intrinsic parameters can be determined linearly after computing the vanishing points of each edges of tri-prism and the coordinates of circular points.

3. CAMERA MODEL

The pinhole model of camera (Figure 1) is geometrically representing the perspective projection; this model is used to project the scene in the image plane. It is characterized by a 3×4 matrix, for the camera i this matrix is defined by $G_i(R_i\ t_i)$:

With:

- $(R_i\ t_i)$ represents the matrix of extrinsic parameters, such as: R_i is the rotation matrix and t_i is the translation vector of camera in space.

- G_i represents the matrix of intrinsic parameters, expressed as follows:

$$G_i = \begin{pmatrix} d_i & s_i & x_{0i} \\ 0 & \mu_i d_i & y_{0i} \\ 0 & 0 & 1 \end{pmatrix}$$

With : d_i is the focal length, μ_i is the scale factor, s_i is the image skew and (x_{0i}, y_{0i}) are the image coordinates of the principal point.

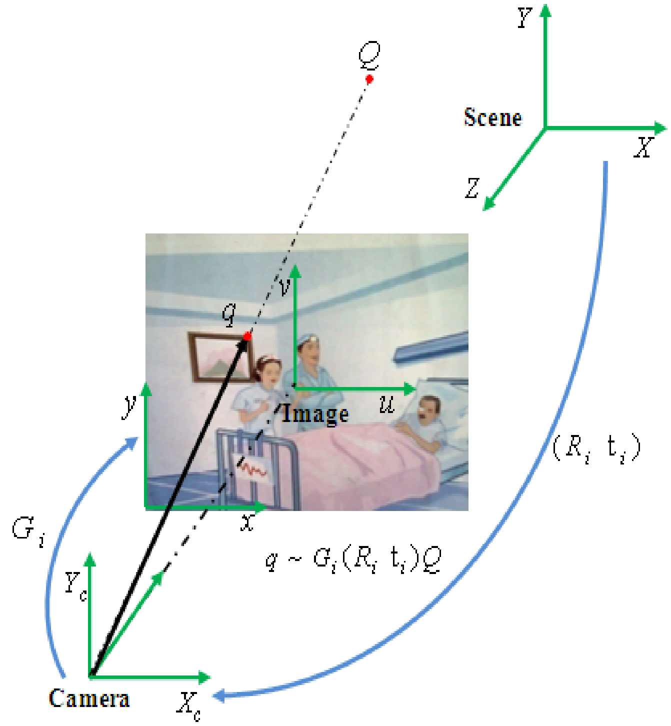

Figure 1. Pinhole model of camera.

4. CAMERAS SELF-CALIBRATION

4.1. control points

Several methods [20, 21, 22, 23] permit to detect the control points in the images, in this work we based on Susan's approach [20]. The latter uses circular masks of pixels which are centred at a point (nucleus), the gray level of nucleus $(I(q_0))$ is compared with each point ($(I(q))$ contained in the mask (1) to define a local area (USAN) of the same gray level as the nucleus, in addition, Susan is based on the response J , which is defined by:

$$J = \begin{cases} \frac{N}{2} - J' & if\ J' < \frac{N}{2} \\ 0 & otherwise \end{cases} \tag{2}$$

With: N is the total number of pixels included in the mask, J' is the size of the USAN area, which is defined by:

$$J' = \sum_{q \in w} K(q) \tag{3}$$

And:

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$$K(q) = e^{-\left[\frac{I(q)-I(q_0)}{g}\right]^6} \quad (2)$$

w is the mask on which a corner will be sought, g is a threshold that corresponds to the minimum contrast of edges. From the response J, if the USAN area is low, the detection of a corner in this area is certain.

4.2. Control points matching

The matching of stereoscopic images [24, 25] is a necessary phase to estimate the parameters of the cameras. The method used in this article is expressed in [24], it is a correlation measure NCC (Normalised Cross Correlation), the main idea of this method is to measure the pixels similarity between pair of images by calculating the correlation score between two windows, the first is fixed to one of the two images, and the second moves in the other image (centred on control point). For a $(2U+1)(2V+1)$ window, the measurement value NCC is expressed by the following formula:

$$NCC(q_1,q_2) = \frac{\sum_{k_1=-U}^{U}\sum_{k_2=-V}^{V} M*M'}{\sqrt{\sum_{k_1=-U}^{U}\sum_{k_2=-V}^{V} M^2 \sum_{k_1=-U}^{U}\sum_{k_2=-V}^{V} M'^2}}$$

With:
$M = I_1(x_{i1}+k_1, y_{i1}+k_2)$, $M' = I_2(x_{j1}+k_1, y_{j1}+k_2)$,
$(q_{i1}, q_{j1}) = ((x_{i1}, y_{i1}), (x_{j1}, y_{j1}))$ are the coordinates of control points in the left and right image, $I_1(q_{i1})$ and $I_2(q_{j1})$ are respectively the gray level of pixels q_{i1} and q_{j1} in both images, $(x_{i1}+k_1, y_{i1}+k_2)$ and $(x_{j1}+k_1, y_{j1}+k_2)$ are the coordinates of neighbours' pixels of control point in the left and right image respectively.

4.3. Estimation of projection matrices

We consider three matches (q_{i1}, q_{j1}), (q_{i2}, q_{j2}) and (q_{i3}, q_{j3}) between the pair of images (Figure 2), which are the projection of three points Q_1, Q_2 and Q_3 of the planar scene. The projection matrices (P_i and P_j) of these three points are determined from the homography matrices and the three matches considered. Therefore, to calculate them: we note by $Q_1Q_2Q_3Q_4$ (it exists an unique Q_4 point) the parallelogram (Figure 2) with centre O and $a_1 = Q_1Q_4$, $a_2 = Q_1Q_2$. We note by π the plane of the planar scene, and we consider a Euclidean reference $\Re(O\ \mathrm{X}\ \mathrm{Y}\ \mathrm{Z})$ fixed on the planar scene and associated to the parallelogram such as: $\mathrm{Z} \perp \pi$.

The homogeneous coordinates of three points Q_1, Q_2 and Q_3 in the reference $(O\ \mathrm{X}\ \mathrm{Y})$ are given as follows:

$Q_1 = (-l_2, -l_3, 1)^T$, $Q_2 = (-l_1, l_3, 1)^T$, $Q_3 = (l_2, l_3, 1)^T$

With:

$l_1 = h_1 - h_2 \cos\phi$, $l_2 = h_1 + h_2 \cos\phi$,

$l_3 = h_2 \sin\phi$, $h_1 = a_1/2$, $h_2 = a_2/2$

And ϕ is the angle between the lines (Q_1Q_2) and (Q_1Q_4).

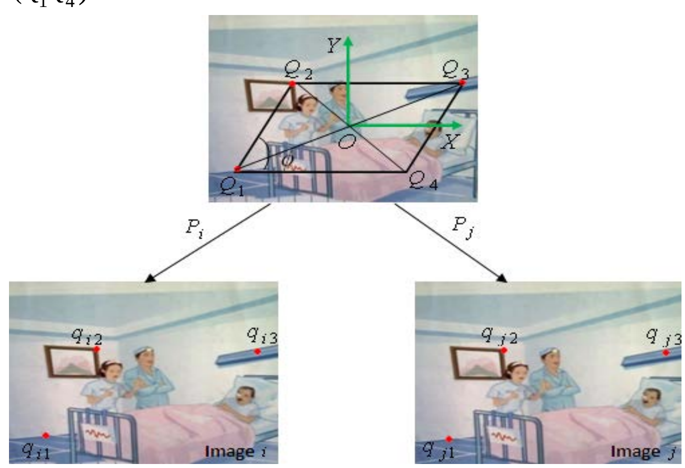

Figure 2. Projection of the parallelogram in the planes of the images i and j.

The projection of the parallelogram in the images i and j by the matrices H_i and H_j gives:

$$q_{im} \cong H_i Q_m \quad (6)$$

$$q_{jm} \cong H_j Q_m \quad (7)$$

With: $m = 1, 2, 3$ and q_{im}, q_{jm} represent respectively the points in the images i and j which are the projections of the vertices Q_1, Q_2

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and Q_3 of the parallelogram, and H_n represents the homography matrix defined by:

$$H_n \sim G_n R_n \begin{pmatrix} 1 & 0 & \\ 0 & 1 & R_n^T t_n \\ 0 & 0 & \end{pmatrix},\ n = i, j \qquad (8)$$

With: G_n represents the matrix of intrinsic parameters, R_n is the rotation matrix and t_n is the translation vector of the camera *n*.

The relations (6) and (7) can be written as:

$$q_{im} \sim H_i L Q'_m \qquad (9)$$

$$q_{jm} \sim H_j L Q'_m \qquad (10)$$

With:

$$L = \begin{pmatrix} h_1 & h_2 \cos\phi & 0 \\ 0 & h_2 \sin\phi & 0 \\ 0 & 0 & 1 \end{pmatrix},\ Q'_1 = \begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix},$$

$$Q'_2 = \begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix} \text{ and } Q'_3 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

We put:

$$P_n \sim H_n L,\ n = i, j$$

With P_i and P_j represent the projections matrices of three points Q'_1, Q'_2 and Q'_3 in the images i and j.

From the equation (11) we can write:

$$P_j \sim H_{ij} P_i \qquad (12)$$

With:

$$H_{ij} \sim H_j H_i^{-1} \qquad (13)$$

The equations (9), (10) and (11) give:

$$q_{im} \sim P_i Q'_m \qquad (14)$$

$$q_{jm} \sim P_j Q'_m \qquad (15)$$

Furthermore, from the equations (12) and (15) we can write:

$$q_{jm} \sim H_{ij} P_i Q'_m \qquad (16)$$

The expressions: (14) and (16) are given according to eight unknowns of P_i, each of these expressions gives six equations with eight unknowns.

So, we can estimate the P_i parameters from these twelve equations with eight unknowns.

The P_j matrix is estimated from the expression (12).

4.4. Self-calibration equations

In this section, we will address the essential phase of our approach, the main idea is to show the relationship between images of the absolute conic (ω_i and ω_j), and the relationship between three matches (q_{im}, q_{jm}), $m = 1, 2, 3$ of each pair of images, these relations give a non-linear cost function, the resolution of this function gives the varying intrinsic parameters of the cameras used.

The expressions (8) and (11) give:

$$P_n \sim G_n R_n \begin{pmatrix} 1 & 0 & \\ 0 & 1 & R_n^T t_n \\ 0 & 0 & \end{pmatrix} L,\ n = i, j \qquad (17)$$

(11)

Therefore, from the previous expression (if : $n = i$), we can write:

$$G_i^{-1} P_i \sim R_i \begin{pmatrix} 1 & 0 & \\ 0 & 1 & R_i^T t_i \\ 0 & 0 & \end{pmatrix} L \qquad (18)$$

If we develop this equation, we obtain:

$$P_i^T \omega_i P_i \sim \begin{pmatrix} L'^T L' & L'^T R_i^T t_i \\ t_i^T R_i L' & t_i^T t_i \end{pmatrix} \qquad (19)$$

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With: $L' = \begin{pmatrix} h_1 & h_2 \cos\phi \\ 0 & h_2 \sin\phi \\ 0 & 0 \end{pmatrix}$, and $\omega_i = \left(G_i G_i^T\right)^{-1}$ is the image of the absolute conic.

The same for P_j:

$$P_j^T \omega_j \; P_j \sim \begin{pmatrix} L'^T L' & L'^T R_j^T t_j \\ t_j^T R_j L' & t_j^T t_j \end{pmatrix} \qquad (20)$$

From the expressions (14) and (16), we can write:

$$q_{jm} \square H_{ij} q_{im} \qquad (21)$$

Therefore:

$$\lambda_{ijm} q_{jm} = H_{ij} q_{im} \qquad (22)$$

With:

$$H_{ij} = \begin{pmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{pmatrix}, \; q_{im} = \begin{pmatrix} x_{im} \\ y_{im} \\ 1 \end{pmatrix}, \; q_{jm} = \begin{pmatrix} x_{jm} \\ y_{jm} \\ 1 \end{pmatrix}$$

And: $\lambda_{ijm} = H_{31} x_{im} + H_{32} y_{im} + H_{33}$

Therefore, from the relation (22), we can write:

$$\lambda_{ijm} q'_{jm} = H_{ij} q'_{im}$$

With:

$$q'_{jm} = \begin{pmatrix} x_{jm} & \frac{H_{12}}{\lambda_{ijm}} & \frac{H_{13}}{\lambda_{ijm}} \\ y_{jm} & \frac{H_{22}}{\lambda_{ijm}} & \frac{H_{23}}{\lambda_{ijm}} \\ 1 & \frac{H_{32}}{\lambda_{ijm}} & \frac{H_{33}}{\lambda_{ijm}} \end{pmatrix} \text{ and}$$

$$q'_{im} = \begin{pmatrix} x_{im} & 0 & 0 \\ y_{im} & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix} \qquad (23)$$

The relation (23) gives:

$$H_{ij} \square q'_{jm} q'^{-1}_{im} \qquad (24)$$

The relations (12) and (20) give:

$$(H_{ij} P_i)^T \omega_j \; (H_{ij} P_i) \sim \begin{pmatrix} L'^T L' & L'^T R_j^T t_j \\ t_j^T R_j L' & t_j^T t_j \end{pmatrix} \qquad (25)$$

Using the last two equations, we can write:

$$(q'_{jm} q'^{-1}_{im} P_i)^T \omega_j \; (q'_{jm} q'^{-1}_{im} P_i) \sim \begin{pmatrix} L'^T L' & L'^T R_j^T t_j \\ t_j^T R_j L' & t_j^T t_j \end{pmatrix} \qquad (26)$$

According to the last expression, we can deduce that the matrices $(q'_{j1} q'^{-1}_{i1} P_i)^T \omega_j \; (q'_{j1} q'^{-1}_{i1} P_i)$ and $(q'_{j2} q'^{-1}_{i2} P_i)^T \omega_j \; (q'_{j2} q'^{-1}_{i2} P_i)$ are identical.

We note by: $C = \begin{pmatrix} c_{11j} & c_{12j} & c_{13j} \\ c_{12j} & c_{22j} & c_{23j} \\ c_{13j} & c_{23j} & c_{33j} \end{pmatrix}$ the matrix corresponding to $(q'_{j1} q'^{-1}_{i1} P_i)^T \omega_j \; (q'_{j1} q'^{-1}_{i1} P_i)$. and: $E = \begin{pmatrix} e_{11j} & e_{12j} & e_{13j} \\ e_{12j} & e_{22j} & e_{23j} \\ e_{13j} & e_{23j} & e_{33j} \end{pmatrix}$ the matrix corresponding to $(q'_{j2} q'^{-1}_{i2} P_i)^T \omega_j \; (q'_{j2} q'^{-1}_{i2} P_i)$.

Therefore, we deduce that:

$$\frac{c_{11j}}{c_{12j}} = \frac{e_{11j}}{e_{12j}}, \; \frac{c_{12j}}{c_{13j}} = \frac{e_{12j}}{e_{13j}}, \; \frac{c_{13j}}{c_{22j}} = \frac{e_{13j}}{e_{22j}}, \; \frac{c_{22j}}{c_{23j}} = \frac{e_{22j}}{e_{23j}}, \; \frac{c_{23j}}{c_{33j}} = \frac{e_{23j}}{e_{33j}} \qquad (27)$$

The previous expression gives:

$$\begin{cases} c_{11j} e_{12j} - e_{11j} c_{12j} = 0 \\ c_{12j} e_{13j} - e_{12j} c_{13j} = 0 \\ c_{13j} e_{22j} - e_{13j} c_{22j} = 0 \\ c_{22j} e_{23j} - e_{22j} c_{23j} = 0 \\ c_{23j} e_{33j} - e_{23j} c_{33j} = 0 \end{cases} \qquad (28)$$

According to the expression (26), we can deduce that the matrices $(q'_{j1} q'^{-1}_{i1} P_i)^T \omega_j \; (q'_{j1} q'^{-1}_{i1} P_i)$ and

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$(q'_{j3}\,q'^{-1}_{i3}\,P_i)^T\,\omega_j\,(q'_{j3}\,q'^{-1}_{i3}\,P_i)$ are identical.

We note by: $B=\begin{pmatrix} b_{11j} & b_{12j} & b_{13j}\\ b_{12j} & b_{22j} & b_{23j}\\ b_{13j} & b_{23j} & b_{33j}\end{pmatrix}$ the matrix corresponding to $(q'_{j3}\,q'^{-1}_{i3}\,P_i)^T\,\omega_j\,(q'_{j3}\,q'^{-1}_{i3}\,P_i)$.

Therefore, we deduce that:

$$\frac{c_{11j}}{c_{12j}}=\frac{b_{11j}}{b_{12j}},\ \frac{c_{12j}}{c_{13j}}=\frac{b_{12j}}{b_{13j}},\ \frac{c_{13j}}{c_{22j}}=\frac{b_{13j}}{b_{22j}},\ \frac{c_{22j}}{c_{23j}}=\frac{b_{22j}}{b_{23j}},\ \frac{c_{23j}}{c_{33j}}=\frac{b_{23j}}{b_{33j}} \qquad (29)$$

The previous expression gives:

$$\begin{cases} c_{11j}b_{12j}-b_{11j}c_{12j}=0\\ c_{12j}b_{13j}-b_{12j}c_{13j}=0\\ c_{13j}b_{22j}-b_{13j}c_{22j}=0\\ c_{22j}b_{23j}-b_{22j}c_{23j}=0\\ c_{23j}b_{33j}-b_{23j}c_{33j}=0\end{cases}$$

According to the expressions (19) and (26) (if $m=1$), we can deduce that the first two rows and columns of matrices $P_i^T\,\omega_i\,P_i$ and $(q'_{j1}\,q'^{-1}_{i1}\,P_i)^T\,\omega_j\,(q'_{j1}\,q'^{-1}_{i1}\,P_i)$ are identical.

We note by: $A=\begin{pmatrix} a_{11i} & a_{12i}\\ a_{12i} & a_{22i}\end{pmatrix}$ the matrix corresponding to the first two rows and columns of $P_i^T\,\omega_i\,P_i$.

Therefore, we deduce that:

$$\frac{c_{11j}}{c_{12j}}=\frac{a_{11i}}{a_{12i}},\ \frac{c_{12j}}{c_{22j}}=\frac{a_{12i}}{a_{22i}} \qquad (31)$$

The previous expression gives:

$$\begin{cases} c_{11j}a_{12i}-a_{11i}c_{12j}=0\\ c_{12j}a_{22i}-a_{12i}c_{22j}=0\end{cases} \qquad (32)$$

According to the expressions (19) and (26) (if $m=2$), we can deduce that the first two rows and columns of matrices $P_i^T\,\omega_i\,P_i$ and $(q'_{j2}\,q'^{-1}_{i2}\,P_i)^T\,\omega_j\,(q'_{j2}\,q'^{-1}_{i2}\,P_i)$ are identical.

Therefore, we deduce that:

$$\frac{e_{11j}}{e_{12j}}=\frac{a_{11i}}{a_{12i}},\ \frac{e_{12j}}{e_{22j}}=\frac{a_{12i}}{a_{22i}} \qquad (33)$$

The previous expression gives:

$$\begin{cases} e_{11j}a_{12i}-a_{11i}e_{12j}=0\\ e_{12j}a_{22i}-a_{12i}e_{22j}=0\end{cases} \qquad (34)$$

According to the expressions (19) and (26) (if $m=3$), we can deduce that the first two rows and columns of matrices $P_i^T\,\omega_i\,P_i$. and
(30)
$(q'_{j3}\,q'^{-1}_{i3}\,P_i)^T\,\omega_j\,(q'_{j3}\,q'^{-1}_{i3}\,P_i)$ are identical.

Therefore, we deduce that:

$$\frac{b_{11j}}{b_{12j}}=\frac{a_{11i}}{a_{12i}},\ \frac{b_{12j}}{b_{22j}}=\frac{a_{12i}}{a_{22i}} \qquad (35)$$

The previous expression gives:

$$\begin{cases} b_{11j}a_{12i}-a_{11i}b_{12j}=0\\ b_{12j}a_{22i}-a_{12i}b_{22j}=0\end{cases} \qquad (36)$$

From the expressions (28), (30), (32), (34), and (36) we obtain the following system of equations:

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$$\begin{cases} c_{11j}e_{12j} - e_{11j}c_{12j} = 0 \\ c_{12j}e_{13j} - e_{12j}c_{13j} = 0 \\ c_{13j}e_{22j} - e_{13j}c_{22j} = 0 \\ c_{22j}e_{23j} - e_{22j}c_{23j} = 0 \\ c_{23j}e_{33j} - e_{23j}c_{33j} = 0 \\ c_{11j}b_{12j} - b_{11j}c_{12j} = 0 \\ c_{12j}b_{13j} - b_{12j}c_{13j} = 0 \\ c_{13j}b_{22j} - b_{13j}c_{22j} = 0 \\ c_{22j}b_{23j} - b_{22j}c_{23j} = 0 \\ c_{23j}b_{33j} - b_{23j}c_{33j} = 0 \\ c_{11j}a_{12i} - a_{11i}c_{12j} = 0 \\ c_{12j}a_{22i} - a_{12i}c_{22j} = 0 \\ e_{11j}a_{12i} - a_{11i}e_{12j} = 0 \\ e_{12j}a_{22i} - a_{12i}e_{22j} = 0 \\ b_{11j}a_{12i} - a_{11i}b_{12j} = 0 \\ b_{12j}a_{22i} - a_{12i}b_{22j} = 0 \end{cases} \qquad (37)$$

The previous expression is non-linear and contains sixteen equations with tine unknowns: five for ω_i and five for ω_j, therefore, to solve it we minimize by the Levenberg-Marquardt algorithm [19] the following non-linear cost function:

$$\min_{\omega_{i,j}} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \begin{pmatrix} \alpha_j^2 + \beta_j^2 + \gamma_j^2 + \lambda_j^2 + \eta_j^2 + \alpha_j'^2 + \beta_j'^2 + \gamma_j'^2 + \\ \lambda_j'^2 + \eta_j'^2 + \phi_{ij}^2 + \tau_{ij}^2 + \psi_{ij}^2 + \chi_{ij}^2 + \delta_{ij}^2 + \varphi_{ij}^2 \end{pmatrix} \qquad (38)$$

With:

$\alpha_j = c_{11j}e_{12j} - e_{11j}c_{12j}, \beta_j = c_{12j}e_{13j} - e_{12j}c_{13j}, \gamma_j = c_{13j}e_{22j} - e_{13j}c_{22j},$

$\lambda_j = c_{22j}e_{23j} - e_{22j}c_{23j}, \eta_j = c_{23j}e_{33j} - e_{23j}c_{33j}, \alpha_j' = c_{11j}b_{12j} - b_{11j}c_{12j},$

$\beta_j' = c_{12j}b_{13j} - b_{12j}c_{13j}, \gamma_j' = c_{13j}b_{22j} - b_{13j}c_{22j}, \lambda_j' = c_{22j}b_{23j} - b_{22j}c_{23j},$

$\eta_j' = c_{23j}b_{33j} - b_{23j}c_{33j}, \phi_{ij} = c_{11j}a_{12i} - a_{11i}c_{12j}, \tau_{ij} = c_{12j}a_{22i} - a_{12i}c_{22j},$

$\psi_{ij} = e_{11j}a_{12i} - a_{11i}e_{12j}, \chi_{ij} = e_{12j}a_{22i} - a_{12i}e_{22j}, \delta_{ij} = b_{11j}a_{12i} - a_{11i}b_{12j},$

$\varphi_{ij} = b_{12j}a_{22i} - a_{12i}b_{22j}$

And: n is the number of images.

The optimization algorithm used is non-linear; so, it requires an initialization step. Therefore, we propose the following constraints on the self-calibration system to determine the initial solution: The pixels are squared, therefore: $\mu_i = \mu_j = 1$, $s_i = s_j = 0$, the principal point is in the centre of the image, therefore: $x_{0i} = y_{0i} = x_{0j} = y_{0j} = 256$ (because the size of images used is 512×512). And the focal lengths (d_i, d_j) are estimated by replacing the parameters $(x_{0i}, y_{0i}, \mu_i, s_i, x_{0j}, y_{0j}, \mu_j, s_j)$ in the expression (37) above.

4.5. Self-calibration algorithm

This section describes the general algorithm to estimate the varying intrinsic parameters of cameras used; this algorithm contains seven main steps, which are:

Step 1: Reading images.

Step 2: Detecting control points by Susan's approach.

Step 3: Matching control points by the correlation measure

NCC.

Step 4: Estimating the homography matrix by four matches using RANSAC algorithm.

Step 5: Estimating the projection matrices of three points which these projections in the different images represent three matches

between pairs of images.

Step 6: Formulating the non-linear cost function (defined according to image elements of the absolute conic of the cameras used).

Step 7: Minimizing the non-linear cost function by Levenberg-Marquardt algorithm to obtain the intrinsic parameters of these cameras.

a. Initialization: the principal point is in the centre of the image, the pixels are squared, and the focal length is determined by solving a linear equations system.

b. Optimization of the non-linear cost function.

5. EXPERIMENTATIONS

5.1. Simulations

A sequence of 512 × 512 images of an unknown planar scene is simulated to test the performance of the new method presented in this paper. The planar

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scene is projected in the different images with Gaussian noise of varying deviation σ which is added to each image point. The homography matrices between pairs of images are determined from four matches by the RANSAC algorithm [18]; they are used with the projection of the three points of the scene on the images planes to estimate the projection matrices of these three points. The control points are detected by Susan's approach [20] and matched in each pair of images by the correlation measure NCC [24], the projection matrices of cameras are used with the three matches to formulate a non-linear cost function, the resolution of this function by the Levenberg-Marquardt algorithm [19] provides the image elements of the absolute conic of different cameras used and finally its intrinsic parameters.

The figure 3 and 4 show the relative error on the focal length according to number of images and noises respectively.

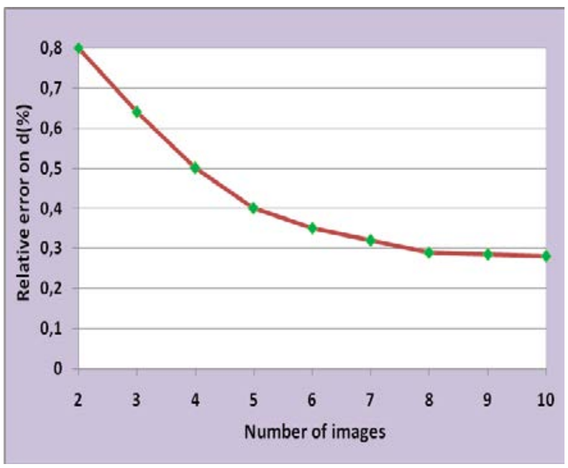

Figure 3. Relative error on d according to number of images.

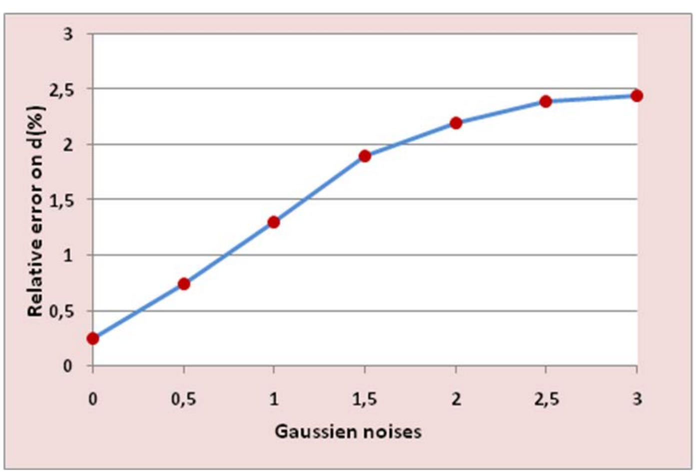

Figure 4. Relative error on d according to noise.

According to figure 3, we can conclude that:

The relative error on the focal length decrease almost linearly if the number of images is between 2 and 5 images, but we see that the relative error decreases slowly if the number of images used is between 5 and 8, and becomes almost stable if the images number exceeds 8.

To show the performance of our method to noise, we added to the pixels of images a Gaussian noise, such as $\sigma <= 3$ pixels. According to Figure 4, we see that the relative error of the focal length increase almost linearly with the increment of noises ($\sigma <= 1{,}5$), but we note that the relative error decreases slowly if $\sigma <= 2{,}5$, and becomes almost stable if $\sigma > 2{,}5$.

And to test the robustness of our method with other approaches, we compared our results with the results obtained by two approaches which are Triggs [1] and Zhang [26]. From the simulations performed, we can say that: while adding noise, our approach gives good results compared to Triggs, and it gives similar results compared to those obtained by Zhang.

5.2. Real data

The experiments were performed on 512×512 images of unknown planar scene (shown in Figure 5) taken by CCD cameras characterized by varying intrinsic parameters.

Figure 5. Two images of unknown planar scene.

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The experiments results, of initial and optimal solutions of intrinsic parameters of cameras used, obtained by our method are shown in Table 1 below:

Table 1. Initialization and optimization of cameras parameters in the case of real scenes.

		d	μ	s	x_0	y_0
Camera 1	***Initial solution***	1120	1	0	256	256
	Optimal solution	1170	0,95	0,02	260	259
Camera 2	***Initial solution***	1115	1	0	256	256
	Optimal solution	1130	0,92	0,03	249	261

From the results of the approach presented in this paper and those obtained by two methods (Triggs [1] and Zhang [26]) which are well-established, we can say that our results are a little different to those obtained by Triggs, and similar to those obtained by Zhang, this shows the performance of our method in terms of accuracy, and demonstrates that our method gives a very good results.

According to the performed experiments, we can say that using only two images gives a strong point to our article in terms of execution time on the one hand, and the speed of convergence to the optimal solution on the other.

The different algorithms used in this article are implemented by the object-oriented programming language that is Java, the main classes that we have programmed in this work are:

- A class to create the menu bar.
- A class to create the toolbar.
- Two classes to read each pair of images.
- A class to load images in the working interface.
- A class for the detection of control points.
- A class for the matching of control points.
- A class for the correction of false matches.
- A class to estimate the homography matrices.
- A class to estimate the projection matrices.
- A class for solving a non-linear cost function.
- Other classes for managing the working interface, events and for mathematical calculations.

In addition, we used several predefined classes in APIs: swing, awt, util, io, jama, etc.

6. CONCLUSION

We treated in this paper a theoretical and practical study of a new method of cameras self-calibration. The importance of this approach is the use of cameras characterized by varying intrinsic parameters. Furthermore, we have shown that two images of a planar scene are sufficient to estimate the different parameters; therefore, we have minimized the constraints on the self-calibration system. The method is based on the demonstration of the relationships between three matches and the relationships between images of absolute conic for each pair of images. From these relationships, we have formulated a non-linear cost functions, its resolution permit to estimate the intrinsic parameters of different cameras used. The simulations performed and the results of experiments show the performance of our method in terms of accuracy and convergence.

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